Deformable Segmentation of Medical Image via Machine Learning

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Outline

1. Background
2. Challenges
3. Sparse learning based lung field segmentation
4. Boundary regression based pelvic organ segmentation
5. Conclusions
Medical image segmentation is important to physicians

- Obtain the structure and functionality of organ and tissue
- Obtain geometric and physical parameters of organ and lesion
- Reconstruct 3D medical image for 3D localization and surgical planning

The accuracy of segmentation largely affects the judgement of physicians on disease, thus, diagnosis and treatment.
Segmentation methods

- Gradient and Laplace operator based edge detection
- Threshold and region growth based region detection
- Deformable Model
  - Active Contour Model
  - Level Set
  - Active Shape Model
Active Shape Model
Challenges

- Due to the imaging mechanism, medical image has noise, artifact and low contrast.

- Due to the organ movement, anatomical complexity, and lesion distraction, organ of interest usually has ambiguous boundary.

- Due to the individual difference, shapes and appearances of different patients are different.
Lung field segmentation in PA chest radiograph
- sparse learning based local shape model
- sparse learning based local appearance model

Prostate and rectum segmentation in CT images
- novel boundary regression based appearance model
Challenges

1）High variation of lung shapes
Challenges

2) Ambiguity of lung boundary
Our method

Sparse Learning based Local Appearance Model → Boundary Ambiguity

Sparse Learning based Local Shape Model → Shape Variation
ASM appearance model

Mahalanobis distance

$$f(g_s) = (g_s - \bar{g})^T S_g^{-1} (g_s - \bar{g})$$
Local appearance model

Motivation
Local appearance model

Algorithm 3-1: Appearance-consistent edge segment partitioning

**Input:** \( \{I_k | k = 1, 2, \ldots, n\} \) - all training images,

- \( p_i^k \) - the coordinate of point \( i \) in the training image \( I_k \),

- \( \beta \) - a coefficient to balance appearance feature and spatial distance in the point similarity measure below

**Output:** \( G' \) boundary segments \( Y'_l (l = 1, 2, \ldots, G') \)

1. **for** each \( k \in \{1, 2, \ldots, n\} \) **do**
2. Compute the appearance feature vector \( f_i^k \) for point \( i (i = 1, 2, \ldots, m) \) on the training image \( I_k \).
3. Compute the similarity matrix \( \Psi^k \) on \( I_k \) using appearance features and spatial distances between points:

\[
\Psi_{i,j}^k = -\|f_i^k - f_j^k\|_2 - \beta\|p_i^k - p_j^k\|_2,
\]

4. where \( \Psi_{i,j}^k \) is the similarity between point \( i \) and point \( j \) on \( I_k \).
5. **end for**
6. Average the similarity matrices on all training images:

\[
\overline{\Psi}_{i,j} = \frac{1}{n} \sum_{k=1}^{n} \Psi_{i,j}^k,
\]

7. Apply affinity propagation algorithm on \( \overline{\Psi} \) to cluster the points into \( G' \) segments.
8. **return** \( G' \) boundary segments \( Y'_l (l = 1, 2, \ldots, G') \)
Sparse Representation based Classification (SRC) on each segment

- Build Discriminative dictionary
  \[
  D^A = [D_L \ D_N]
  \]

- Sparse Representation
  \[
  \arg\min_c \|b - D^A c\|_2^2 + \lambda \|c\|_1
  \]

- Classification based on residuals
  \[
  r_L = b - D_L c_L, \quad r_N = b - D_N c_N, \quad r = [r_L^T \ r_N^T]^T
  \]

  \[
  J(\alpha, \rho) = \sum_{i=1}^{n'} \log \left( 1 + \exp \left( -z_{y_i}(\alpha^T r_{y_i} + \rho) \right) \right) + \varphi \|\alpha\|_2
  \]

  \[
  h(y) = \frac{1}{1 + \exp\left( -((\hat{\alpha}^T r_y + \hat{\rho}) \right)}
  \]
Local Appearance Model

- Local Appearance-guided Deformation

Find a best position in a search range
PCA Shape Model

\[ S = (x_1, y_1, \ldots, x_n, y_n)^T \]  \hspace{1cm} (1)

\[ \hat{S} = \bar{S} + Pb \]  \hspace{1cm} (2)

\[ b = P^T (S' - \bar{S}) \]  \hspace{1cm} (3)
Motivation  global sparse shape composition (SSC)

\[
\arg \min_c \|b - D^S c\|_2^2 + \lambda \|c\|_1,
\]

\[
b \approx D^S c
\]

Limitation of  global sparse shape composition

- deformed organ boundary
- refined organ boundary by SSC
- manually segmented boundary
Local Shape Model

算法 4-1 变化一致的形状段的划分

Input: \( \{S_k | k = 1, 2, \ldots, n \} \) - the training shapes,

\( p_i^k \) - the coordinate of point \( i \) in the training shape \( S_k \),

\( \gamma \) - a coefficient to balance position variation and spatial distance in the point similarity measure below

Output: \( G \) shape segments \( Y_l (l = 1, 2, \ldots, G) \)

1: Align all shapes \( S_k \) into a common space by Procrustes analysis. (\( \hat{p}_i^k \) is the counterpart of \( p_i^k \) after alignment)

2: Calculate the position variation of each point across training shapes:

\[
v_i = \frac{1}{n} \sum_{k=1}^{n} \| \hat{p}_i^k - \mu_i \|_2, \mu_i = \frac{1}{n} \sum_{k=1}^{n} \hat{p}_i^k
\]

3: Compute the similarity matrix \( \psi \) based on position variation and spatial distance:

\[
\psi_{i,j} = -|v_i - v_j| - \gamma \| \mu_i - \mu_j \|_2
\]

4: where \( \psi_{i,j} \) is the similarity between point \( i \) and point \( j \).

5: Apply affinity propagation algorithm on \( \psi \) to cluster the points into \( G \) segments.

6: return \( G \) shape segments \( Y_l (l = 1, 2, \ldots, G) \)
✓ Build dictionary $D^S_l$ for each segment on training set

$$D^S_l = [\hat{Y}_l^1 \hat{Y}_l^2 \ldots \hat{Y}_l^n]$$

✓ Constrain a deformed shape $b$ by sparse representation

$$\arg \min_{c_l} \| b_l - D^S_l c_l \|_2^2 + \lambda_l \| c_l \|_1 \quad l = 1, 2, \ldots, G$$

Note:
$G=1$, conventional SSC.
Experiments

- Open JSRT dataset
- 247 Posterior-Anterior chest radiology
- 2048 x 2048, 0.175 mm/pixel, 12-bit
- 94 annotated landmarks
  (left 50, right 44)
Experiments

Local appearance model vs Gaussian appearance model

- automatically segmented boundary
- manually segmented boundary
### Experiments

Quantitative comparison between Gaussian-based appearance model and local appearance model

<table>
<thead>
<tr>
<th>Method</th>
<th>Overlap ±std</th>
<th>Min Overlap</th>
<th>Median Overlap</th>
<th>Max Overlap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian-based appearance model</td>
<td>0.910±0.080</td>
<td>0.584</td>
<td>0.937</td>
<td>0.965</td>
</tr>
<tr>
<td>Local appearance model</td>
<td>0.946±0.019</td>
<td>0.814</td>
<td>0.948</td>
<td>0.968</td>
</tr>
</tbody>
</table>
Experiments

PCA shape model

Global SSC shape model

Local SSC shape model

- deformed organ boundary
- refined organ boundary
- manually segmented boundary
### Experiments

#### Quantitative comparison between PCA, global SSC and local SSC

<table>
<thead>
<tr>
<th>Method</th>
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<th>Max Overlap</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>0.920±0.032</td>
<td>0.771</td>
<td>0.929</td>
<td>0.962</td>
</tr>
<tr>
<td>Global SSC</td>
<td>0.927±0.025</td>
<td>0.793</td>
<td>0.933</td>
<td>0.959</td>
</tr>
<tr>
<td>Local SSC</td>
<td>0.946±0.019</td>
<td>0.814</td>
<td>0.948</td>
<td>0.968</td>
</tr>
</tbody>
</table>
Experiments

Comparison with state-of-the-art methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Overlap</th>
<th>ACD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dawoud et al.</td>
<td>0.940±0.005</td>
<td>2.460±2.060</td>
</tr>
<tr>
<td>Coppini’s method</td>
<td>0.927±0.033</td>
<td>1.730±0.870</td>
</tr>
<tr>
<td>Tan’s method</td>
<td>0.883±0.035</td>
<td>N/A</td>
</tr>
<tr>
<td>Shi’s method</td>
<td>0.920±0.031</td>
<td>2.492±1.092</td>
</tr>
<tr>
<td>Human Observer</td>
<td>0.946±0.018</td>
<td>1.640±0.690</td>
</tr>
<tr>
<td>Proposed Method</td>
<td>0.946±0.019</td>
<td>1.669±0.762</td>
</tr>
</tbody>
</table>

Note: ACD denotes Average Contour Distance
• Lung field segmentation in PA chest radiograph
  + sparse learning based local shape model
  + sparse learning based local appearance model

• Prostate and rectum segmentation in CT images
  + novel boundary regression based appearance model
The segmentation of prostate and nearby organs in CT images is a prerequisite for image-guided radiation treatment of prostate cancer.

**Challenges:**
- Low image contrast
- Variable appearance and shape

(a) A CT slice of a patient
(b) The same CT slice with annotated organs
(c) A slice of another patient, with more bowel gas

Prostate  Rectum
Our method

Regression Forest

\[ \hat{d} = (\Delta x, \Delta y, \Delta z) \]

rough object location, landmark detection, deformable segmentation (recently).
Boundary Regression

Boundary Regression and Voting

Landmark regression and voting

Target prostate boundary

Boundary regression

Boundary voting map
- **Appearance features** are the 3D Haar features extracted from original image.
- **Context features** are also the 3D Haar features extracted from the displacement map of the previous regression forest.
Auto-context Model

Transverse view

Sagittal view

Coronal view

Iteration#1  Iteration#3  Iteration#5

manually segmented boundary
Flow chart of boundary-voting-guided deformable segmentation
Experiments

**Dataset:** 70 planning CT images from 70 patients
voxel size: $0.938 \times 0.938 \times 3.0 \text{ mm}^3$, resampled: $2.0 \times 2.0 \times 2.0 \text{ mm}^3$

**Parameter Setting:**
- Number of regression trees 10;
- Maximal depth of each tree 15;
- Patch size for extracting Haar feature 30x30x30;
- Sample# of each training image $N = 10000$;
- Iteration# in the auto-context model is 5 (i.e., $K = 4$);
- PCA shape space capture 98%;
- Iteration# of deformable segmentation 20.
## Boundary Regression VS Boundary Classification

<table>
<thead>
<tr>
<th>Method</th>
<th>Original Image</th>
<th>Classification result</th>
<th>Voting result</th>
<th>Segmentation of classification result</th>
<th>Segmentation of voting result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prostate</td>
<td>![Prostate Image]</td>
<td>![Prostate Classification]</td>
<td>![Prostate Voting]</td>
<td>![Prostate Segmentation]</td>
<td>![Prostate Segmentation]</td>
</tr>
<tr>
<td>Rectum</td>
<td>![Rectum Image]</td>
<td>![Rectum Classification]</td>
<td>![Rectum Voting]</td>
<td>![Rectum Segmentation]</td>
<td>![Rectum Segmentation]</td>
</tr>
<tr>
<td><strong>Boundary classification</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prostate</td>
<td>![Prostate Image]</td>
<td>![Prostate Classification]</td>
<td>![Prostate Voting]</td>
<td>![Prostate Segmentation]</td>
<td>![Prostate Segmentation]</td>
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<td>Rectum</td>
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<td>![Rectum Classification]</td>
<td>![Rectum Voting]</td>
<td>![Rectum Segmentation]</td>
<td>![Rectum Segmentation]</td>
</tr>
<tr>
<td><strong>Boundary regression</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prostate</td>
<td>![Prostate Image]</td>
<td>![Prostate Classification]</td>
<td>![Prostate Voting]</td>
<td>![Prostate Segmentation]</td>
<td>![Prostate Segmentation]</td>
</tr>
<tr>
<td>Rectum</td>
<td>![Rectum Image]</td>
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<td>![Rectum Voting]</td>
<td>![Rectum Segmentation]</td>
<td>![Rectum Segmentation]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Method</th>
<th>DSC</th>
<th>ASD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boundary classification</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prostate</td>
<td>0.82±0.07</td>
<td>2.37±0.95</td>
</tr>
<tr>
<td>Rectum</td>
<td>0.76±0.06</td>
<td>3.36±0.09</td>
</tr>
<tr>
<td>Boundary regression</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prostate</td>
<td>0.88±0.02</td>
<td>1.86±0.21</td>
</tr>
<tr>
<td>Rectum</td>
<td>0.84±0.05</td>
<td>2.21±0.50</td>
</tr>
</tbody>
</table>

- automatically segmented boundary
- manually segmented boundary
### Experiments

#### Comparison with other state-of-art methods (on prostate)

<table>
<thead>
<tr>
<th>Method</th>
<th>Mean SEN</th>
<th>Median SEN</th>
<th>Mean ASD</th>
<th>Median ASD</th>
<th>Mean PPV</th>
<th>Median FPR</th>
<th>Mean DSC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chen et al. [1]</td>
<td>NA</td>
<td>0.84</td>
<td>NA</td>
<td>1.10</td>
<td>NA</td>
<td>0.13</td>
<td>NA</td>
</tr>
<tr>
<td>Costa et al. [2]</td>
<td>0.75</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>0.80</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Martínez et al. [3]</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>0.87</td>
</tr>
<tr>
<td>Lu et al. [4]</td>
<td>NA</td>
<td>NA</td>
<td>2.37</td>
<td>2.15</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Our method</td>
<td>0.84</td>
<td>0.87</td>
<td>1.86</td>
<td>1.85</td>
<td>0.86</td>
<td>0.06</td>
<td>0.88</td>
</tr>
</tbody>
</table>

**NA** indicates that the respective metric was not reported in the publication. The unit of ASD is mm.

Experiments

Comparison with other state-of-art methods (on *rectum*)

<table>
<thead>
<tr>
<th>Method</th>
<th>Mean SEN</th>
<th>Median SEN</th>
<th>Mean ASD</th>
<th>Median ASD</th>
<th>Mean PPV</th>
<th>Median FPR</th>
<th>Mean DSC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chen et al. [1]</td>
<td>NA</td>
<td>0.71</td>
<td>NA</td>
<td>2.20</td>
<td>NA</td>
<td>0.24</td>
<td>NA</td>
</tr>
<tr>
<td>Martínez et al. [3]</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>0.82</td>
</tr>
<tr>
<td>Lu et al. [4]</td>
<td>NA</td>
<td>NA</td>
<td>4.23</td>
<td>4.09</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Our method</td>
<td>0.72</td>
<td>0.75</td>
<td>2.21</td>
<td>2.26</td>
<td>0.76</td>
<td>0.18</td>
<td>0.84</td>
</tr>
</tbody>
</table>

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Conclusions

- Lung field segmentation in PA chest radiograph
  + sparse learning based local shape model
  + sparse learning based local appearance model

- Prostate and rectum segmentation in CT images
  + novel boundary regression based appearance model
Thank you